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IMPROVED SEISMIC CLASSIFIERS

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Donald F. Roberts**

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13. ABSTRACT This report describes the design and evaluation of classifiers for distinguishing humans, vehicles, aircraft, and background alarms based on seismic disturbances. The design and evaluation was performed by RADC (ISCP) using the On-Line Patter Analysis and Recognition System (OLPARS). The data base, supplied by RADC (COTI), consisted of a set of measurements extracted from seismometer responses to each of the intruding targets.			

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FOREWORD

The improved seismic designs discussed in this report are based entirely on data supplied by RADC (COTI) and their contractors. Without their preparation of this data base, no work would have been possible.

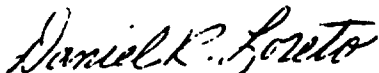
Secondly, the importance of the OLPARS System cannot be underestimated. Without this large interactive system, with its library of mathematical and/or graphical options, no classifier designs would have been possible in this short period of time.

This work was conducted under the Advanced Development Program Job Order Number 692B0000. The report has been reviewed by Mr. Robert Curtis, Project Engineer, and has been designated as unclassified material.

This report has been reviewed by the Information Office (OI) and is releasable to the National Technical Information Service NTIS).

This technical report has been reviewed and is approved.

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ABSTRACT

This report describes the design and evaluation of classifiers for distinguishing humans, vehicles, aircraft and background alarms based on seismic disturbances. The design and evaluation was performed by RADC (ISCP) using the On-Line Pattern Analysis and Recognition System (OLPARS). The data base, supplied by RADC (COTI), consisted of a set of measurements extracted from seismometer responses to each of the intruding targets.

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SECTION I

INTRODUCTION

The report discusses the design and evaluation of two classifiers to distinguish human intrusions, vehicular intrusions, aerial intrusions, and/or background alarms based on seismic disturbances. The design is based on data supplied by RADC (COTI). The data consisted of a set of measurements extracted from the outputs of vertical axis seismometers. Consequently, the design by RADC (ISCP) was restricted to starting with a preselected set of segmentation criteria and features already incorporated into the data base.

The main results consist of:

- . An increase in the probability of detection (on the design set) from 83.6% to 95% over the previously supplied three-class design.
- . A reduction in design set error rate of 33% over the previously supplied COTI three-class design (humans, vehicles, and nuisances). The error rate is defined as the percentage of samples misclassified. Although a further reduction in the design set error rate is possible, no additional improvement in field performance could be expected.
- . Independent testing which gives a much better estimate of field performance.
- . A new classifier which identifies aerial intrusions as a separate class.

- . One design which may be used as a 2-, 3-, or 4-class classifier with the simple addition/deletion of OR-gate connections.

SECTION II

THE DATA BASE

The data base supplied by COTI consists of a set of seventeen (17) measurements extracted from the raw seismic data. The measurements consisted of eight Time-Between-Event-Histogram Cells (TBE), eight Time-Between-Zero Crossing Histogram Cells (ZC), and the time period for which a preliminary segmentation algorithm indicated that an event of interest was present. Table II-1 gives further details on these measurements.

The classes consisted of (1) single humans walking or running at various ranges, (2) wheeled vehicles at various speeds, ranges, and weights, (3) false outputs of the segmentation routine caused by environmental disturbances, such as noise, wind, rain, or lightning, and (4) helicopters and aircraft (both prop and jet) at various altitudes and speeds.

TABLE II-1 FEATURES TABLE

<u>TIME-BETWEEN-EVENT CELLS (MS)</u>		<u>COTI-DESIGN FEATURES</u>	<u>ISCP-DESIGN FEATURES</u>
1	200-280	1	1/17*
2	280-360	2	2/17
3	360-440	3+4	3/17
4	440-520		4/17
5	520-600	5+6	5/17
6	600-680		6/17
7	680-760	7+8	7/17
8	≥ 760		8/17
 <u>ZERO-CROSSING CELLS (MS)</u>			
9	0-12	9	9/17
10	12-24	10	10/17
11	24-36		11/17
12	36-48		12/17
13	48-60		13/17
14	60-72	13+14+15+16	14/17
15	72-84		15/17
16	≥ 84		16/17
 <u>TIME ON</u>			
17			17

*Division by feature 17, normalizes the feature on a per time basis.

SECTION III

THREE CLASS CLASSIFIERS

A. COTI - SUPPLIED DESIGN

In the three-class problem, the background and aerial intrusions are treated as a single class labeled nuisances (N). Using the COTI-Supplied design logic, the data supplied by COTI was checked and a confusion matrix was prepared on a run, as opposed to an intrusion, basis. Some clarification of intrusion and run basis is needed. Due to the COTI-Supplied segmentation routines, it is possible for either a single human or a single vehicular intrusion to cause the classifier to trigger and output a string or sequence of decisions. A single output is called a run. Although results discussed elsewhere are on a run basis, this report emphasizes results on an intrusion basis since in the field there exists no method for defining an intrusion as a unique entity. However, there is little difference between either method of tabulating results.

Table III-I shows the confusion matrix and associated classification and error rates for the COTI supplied design. It is emphasized that these rates are the design set rates only, and that design set rates tend to be optimistic (see Foley [1]).

TABLE III-1 COTI THREE CLASS DESIGN SET RESULTS
(RUN BASIS)

		ASSIGNED CLASS			<u>NO. OF RUNS</u>
		<u>H</u>	<u>V</u>	<u>N</u>	
TRUE CLASS	Human (H)	301	16	85	402
	Vehicle (V)	12	168	13	193
	Nuisance (N)	6	54	1059	1119
					<hr/> 1714

$$P_{\text{Correct Classification}} = \text{Prob} \{H \text{ is } H \text{ or } V \text{ is } V \text{ or } N \text{ is } N\} = \frac{1528}{1714} = 89.1\%$$

$$P_{\text{Detection}} = \text{Prob} \{H \text{ or } V \text{ is called } H \text{ or } V\} = \frac{497}{595} = 83.6\%$$

$$P_{\text{False Alarm}} = \text{Prob} \{N \text{ is } V \text{ or } H\} = \frac{60}{1119} = 5.4\%$$

B. ISCP THREE-CLASS DESIGN

The design by ISCP was restricted by the data base supplied by COTI in the following:

1. Only the classes on which data was collected could be identified.
2. ISCP was restricted to using the basic features or measurements extracted.

It became obvious that each of the first sixteen measurements which were collected over a period of time which varied from 3 to 32 seconds, needed some form of time normalization to reduce the wide within-class variance of each measurement. Consequently, the first sixteen features were normalized by dividing by the time-on measurement (# 17). Therefore, the zero crossing and time-between-event measurements are now on a unit time basis. Based on this normalized set of measurements, the On-Line Pattern Analysis and Recognition System (OLPARS), (reference Sammon [2]), was used to design entirely new classification logic. This logic consists solely of sets of linear discriminants for ease of hardware implementation. The logic is based on the pairwise Fisher Linear Discriminant Technique.

For each pair of classes i and j , a unit vector d_{ij} is computed such that projections of the data d_{ij} maximizes the ratio of the between-class scatter to the within-class scatter.

It has been shown that the direction \underline{d}_{ij} which maximizes this ratio is given by [2]

$$\underline{d}_{ij} = \alpha \underline{W}_{ij} \underline{\Delta}_{ij}$$

where $\underline{W}_{ij} = (N_i - 1) C_i + (N_j - 1) C_j$

C_i = Estimated covariance matrix for class i

$$\underline{\Delta}_{ij} = \underline{\mu}_i - \underline{\mu}_j$$

$\underline{\mu}_i$ = Estimated mean vector of class i

and α is a normalizing constant so that $|\underline{d}| = 1$

OLPARS computes \underline{d}_{ij} for all possible pairs of classes and establishes an initial threshold.

$$\theta_{ij} = \left(\frac{\underline{\mu}_i + \underline{\mu}_j}{2} \right)^T (\underline{\mu}_i - \underline{\mu}_j)$$

The classification rule for the pairs of classes i, j is given by

$$\underline{x}^T \underline{d}_{ij} > \theta_{ij} \Rightarrow \underline{x} \text{ is a member of class } i$$

where \underline{x} is the ordered set of measurements

The θ_{ij} computed by OLPARS may be adjusted by the user to obtain optimal discrimination along each \underline{d}_{ij} . A frequency histogram of the sample vectors projected on the appropriate discriminants can be displayed for each pair of classes. The histogram is obtained by summing the number of sample vectors that fall in each of 120 bins that span the range of the projections. For viewing purposes, the frequency bins are displayed as 40 or less columns

of characters on the CRT. The θ_{ij} computed by the system is displayed as a vertical line on the CRT. The user can adjust the θ_{ij} by designating a display column on the CRT or more accurately by inputting a specific bin number. A hardcopy of the projected data values versus bin number is provided by the system to assist the user in selecting an optimal threshold.

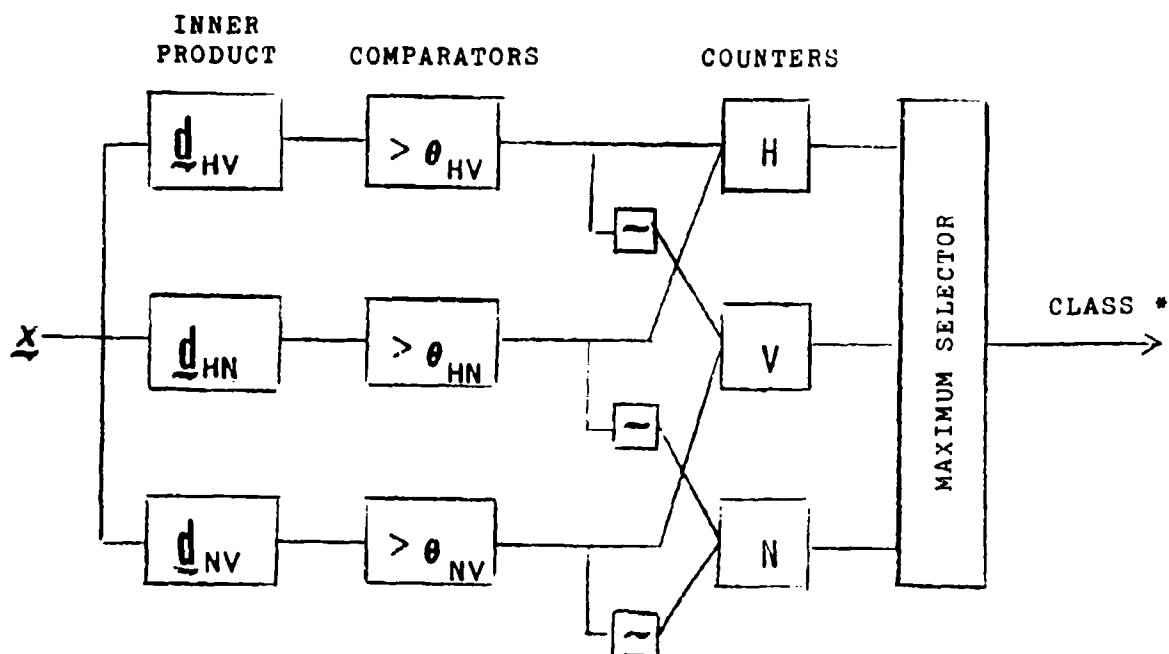
The discriminant vectors, weights and thresholds for each pair of classes are given in Appendix A. The input consists of the normalized set of 17 features given in Table II-1. Each input vector is classified using the scheme diagramed in Figure III-1. Although the logic scheme is shown for three classes, it may be easily extended to an arbitrary number of classes. Table III-2 shows the results of the ISCP designed logic.

C. COMPARISON AND ERROR ANALYSIS

The main improvements are an increase in the probability of detection from 83.6% to 95% and a 33% reduction in the Error Rate from 10.9% to 7.3%. The relatively small increase in the probability of false alarm is not considered significant when compared to the increase in the probability of detection. The decision was made to allow 9 more false alarms so that 68 more detections could be realized. These are design set rates. As pointed out [1], these predictors of performance may be optimistic estimates of field performance. However, since this is the only estimate used in the previously supplied design, these estimates are the only available means of comparison.

It is possible for ISCP to "over-design" on the data base in order to lower the design set error rate. However, these changes

PAIRWISE FISHER LOGIC



H: Human

V: Vehicle

N: Nuisance (i.e., Background or Aircraft)

X: Unknown Input (i.e. output of the segmentation and feature extractor device)

d : Linear Discriminant

θ : Threshold

\sim : Inverter

FIGURE III-1

*If vote is tied, assign input to class with the highest a priori probability.

could not be expected to improve the field performance of the device. The errors are present due to the somewhat unpredictable multiple turn-on/turn-off criteria used. For instance, the time-between-events histogram feature was chosen in order to discriminate the class of humans from the remaining classes. The distinguishing characteristics for the human class were hypothesized to be significant entries in the higher order cells due to the sequence of footsteps. Consider human intrusion number 626, run numbers one and five as given in Table III-3.*

<u>T-B-E Cell Numbers</u>	<u>RUN # 1</u>	<u>RUN # 5</u>
1. 200-280 MS	159	54
2. 280-360	0	1
3. 360-440	0	3
4. 440-520	0	1
5. 520-600	0	7
6. 600-680	0	19
7. 680-760	0	3
8. ≥ 760	0	1

TIME-BETWEEN-EVENT FEATURES FOR HUMAN INTRUSION 626

TABLE III-3

*Since only runs 1 and 5 were supplied, it is assumed that the missing run numbers are due to non-seismic disturbances.

ISCP THREE-CLASS DESIGN SET RESULTS

(RUN BASIS)

		ASSIGNED CLASS			<u>NO. OF RUNS</u>
		<u>H</u>	<u>V</u>	<u>N</u>	
TRUE CLASS	Human (H)	363	17	22	402
	Vehicle (V)	9	176	8	193
	Nuisance (N)	23	46	1050	1119
					<hr/>
					1714

$P_{\text{Correct Classification}} = \text{Prob \{H is H or V is V or N is N\}} =$

$$\frac{1589}{1714} = 92.7\%$$

$P_{\text{Detection}}$

$$= \text{Prob \{H or V is H or V\}} = \frac{565}{595} = 95\%$$

$P_{\text{False Alarm}}$

$$= \text{Prob \{N is H or V\}} = \frac{69}{1119} = 6.2\%$$

TABLE III-2

could not be expected to improve the field performance of the device. The errors are present due to the somewhat unpredictable multiple turn-on/turn-off criteria used. For instance, the time-between-events histogram feature was chosen in order to discriminate the class of humans from the remaining classes. The distinguishing characteristics for the human class were hypothesized to be significant entries in the higher order cells due to the sequence of footsteps. Consider human intrusion number 626, run numbers one and five as given in Table III-3.*

<u>T-B-E Cell Numbers</u>	<u>RUN # 1</u>	<u>RUN # 5</u>
1. 200-280 MS	159	54
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3. 360-440	0	3
4. 440-520	0	1
5. 520-600	0	7
6. 600-680	0	19
7. 680-760	0	3
8. ≥ 760	0	1

TIME-BETWEEN-EVENT FEATURES FOR HUMAN INTRUSION 626

TABLE III-3

*Since only runs 1 and 5 were supplied, it is assumed that the missing run numbers are due to non-seismic disturbances.

First notice the large differences in the numerical values of features for two runs from the same intrusion. Second, notice that while footsteps are evident in run 5, none are evident in run 1.

As a second example, consider vehicular intrusion number 402, runs 4 and 7 (again these are the only seismic runs supplied) given in Table III-4. Run 4 contains little, if any, indication of footsteps and is assigned by the OLPARS logic to the class of vehicles. However, run 9 indicates footsteps, and (we submit) is "correctly" classified as a man. The point is:

The logic is performing exactly as it should, if it assigns spurious outputs of the segmentation logic to the classes these spurious outputs most closely resemble. In other words, these errors are inherent in the data base, and we submit that these errors are due to unpredictable outputs of the multiple turn-on/turn-off segmentation criteria.

TIME-BETWEEN-EVENTS FEATURES FOR VEHICULAR INTRUSION 402

TABLE III-4

<u>T-B-E Cell Numbers</u>	<u>RUN # 4</u>	<u>RUN # 9</u>
1. 200-280	39	2
2. 280-360	2	0
3. 360-440	2	1
4. 440-520	0	3
5. 520-600	0	17
6. 600-680	0	19
7. 680-760	0	6
8. ≥ 760	2	3

Appendix B gives the usefulness of each feature for discriminating each pair of classes. The ranking procedure measures the overlap for each pair of classes along each feature. This procedure called the Probability of Confusion Measure is a histogram approximation of the class distributions along each feature. The technique is particularly useful for data sets in which the modality is unknown since it is independent of mean and variance statistics.

The procedure yields three measures for each feature:

- (1) a pairwise measure for differentiating class i from class j ,
- (2) a measure for differentiating class i from all other classes,
- and (3) a measure of significance for each feature for differentiating each pair of classes [4].

These feature ratings demonstrate an interesting point. Although it has been hypothesized that the higher order time-between-event cells were useful in discriminating humans, Probability of Confusion Measure rates these as the poorest features for this purpose.

D. INDEPENDENT TESTING OF ISCP DESIGN

Although a large number of samples were supplied for each class, it is always prudent to use independent (different) data for the design and testing of the classifier. It is also important to note that it is possible to test the logic without having to implement the device. Independent testing has been shown to be a better estimate (i.e. an unbiased estimate) of the field performance of the design (e.g. Foley [1]).

Although no independent testing of the supplied design was conducted, the following results on the ISCP design are available. The design and test sets each consisted of approximately 50% of the data base selected on a random basis. Table III-5 shows the design and test set results.

The Tables III-2 and III-5 can be interrupted in the following manner. The expected field results should be greater than the test results on half the data (Table III-5), but less than the design results on all the data (Table III-2). For example, the probability of detection should lie between 91.7% and 95.0%.

DESIGN AND TEST RESULTS

<u>DESIGN SET</u>					<u>TEST SET</u>				
	<u>H</u>	<u>V</u>	<u>N</u>	<u>TOTAL</u>		<u>H</u>	<u>V</u>	<u>N</u>	<u>NO. OF RUNS</u>
H	183	7	9	199	H	183	6	14	203
V	2	89	3	94	V	12	76	21	99
N	13	19	527	559	N	17	32	511	560
				<hr/> 852					<hr/> 862

$$P_{cc} = \frac{799}{852} = 93.8\%$$

$$P_{cc} = \frac{771}{862} = 89.3\%$$

$$P_d = \frac{281}{293} = 95.9\%$$

$$P_d = \frac{277}{302} = 91.7\%$$

$$P_{FA} = \frac{32}{559} = 5.7\%$$

$$P_{FA} = \frac{49}{560} = 8.7\%$$

TABLE III-5

SECTION IV

FOUR-CLASS CLASSIFIER

For this classifier, the classes of interest are humans, vehicles, aerial intrusions, and background disturbances. The data for aerial intrusions include helicopters, and both prop and jet aircraft.

Usually when a classifier is designed, features (measurements) are chosen which hopefully contain discriminatory information for each class. Since the features were previously selected for only three classes, no features could be selected with the intention of identifying aircraft. Despite this handicap, a four-class classifier was designed and the results are given in Table III-6 for the design set results on the entire data. Table III-7 contains the results where half the data was used for design and half for test. Notice that the definition of detection, classification, and false alarm change, since a new class has been added.

The majority of errors, approximately 9%, are due to the class of aerial intrusions. In fact, these results are quite encouraging since another study indicated that the addition of new classes seriously effect the recognition accuracies. The addition of features for distinguishing between prop aircraft, jet aircraft, and helicopters offers the possibility of even better classifiers.

DESIGN SET RATES ON ENTIRE DATA SET

		ASSIGNED CLASS					
		<u>H</u>	<u>V</u>	<u>B</u>	<u>A</u>	<u>NO. OF RUNS</u>	
True Class	Humans	H	363	17	10	12	402
	Vehicles	V	9	176	0	8	193
	Background	B	10	4	339	67	420
	Aerial In- trusion	A	13	42	81	563	699
							<hr/>
							1714

$$P_{CC} = \text{Prob} \{H \text{ is } H \text{ or } A \text{ is } A \text{ or } B \text{ is } B \text{ or } V \text{ is } V\} = \frac{1441}{1714} = 84.1\%$$

$$P_D = \text{Prob}\{(H \text{ or } V \text{ or } A)\} = \frac{1203}{1294} = 92.9\%$$

$$P_{FA} = \text{Prob} \{B \text{ is } (H \text{ or } V \text{ or } A)\} = \frac{81}{420} = 19.3\%$$

TABLE III-6

DESIGN AND TEST SET RESULTS

<u>DESIGN</u>						<u>TEST</u>					
	<u>H</u>	<u>V</u>	<u>B</u>	<u>A</u>	<u># OF RUNS</u>		<u>H</u>	<u>V</u>	<u>B</u>	<u>A</u>	<u># OF RUNS</u>
H	182	7	4	5	199	H	183	6	8	6	203
V	2	89	0	3	94	V	12	76	1	10	99
B	6	1	173	30	210	B	7	3	164	36	210
A	7	18	39	285	349	A	10	29	38	273	350
					<hr/>						<hr/>
					852						862

$$P_{cc} = \frac{729}{852} = 85.5\%$$

$$P_{cc} = \frac{696}{862} = 80.7\%$$

$$P_d = \frac{528}{542} = 93.1\%$$

$$P_d = \frac{605}{652} = 92.7\%$$

$$P_{FA} = \frac{27}{210} = 17.6\%$$

$$P_{FA} = \frac{46}{210} = 21.9\%$$

TABLE III-7

SECTION V

DISCUSSION AND RECOMMENDATIONS

This report demonstrates the capability of ISCP to design superior classification logic, using the OLPARS System, in short periods of time given a vector data base. Of course, the quality of the classifier cannot exceed the quality and universality of the input data base. It appears that further improvements in classifier designs will require new and improved segmentation procedures and additional and more relevant features.

However, one possible extension using the present data base may yield a further improvement. For a single intrusion the segmentation procedure may yield multiple outputs or runs. In general, the runs corresponding to strong signals are classified correctly. However, due to the somewhat unpredictable nature of the segmentation procedure, weak runs can result and are incorrectly classified. In the present system, each run is given equal weight. However, it is possible to create regions of either rejection or low confidence. If this strategy were implemented, the user of the system could be supplied not only with a sequence of decisions, but also information indicating the level of confidence in each decision.

APPENDIX A WEIGHT VECTORS

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FISHER LOGIC

NODES IN SET

MAN M VEH V BAC B AER A

PAIR 1 + NODE VEH V - NODE MAN M FISHER

COEFFICIENTS

3.79931943E-01 8.44959634E-02 -7.03530802E-02 -1.38536664E-01 -6.74505955E-02
2.51549479E-02 -1.65137017E-01 -5.01433282E-02 5.07081962E-02 7.59342792E-02
1.03744971E-01 1.62500179E-01 3.03479490E-01 4.41463384E-01 4.62519497E-01
4.75203523E-01 1.50908957E-01

THRESHOLDS

5.34253940E 00

PAIR 2 + NODE BAC B - NODE MAN M FISHER

COEFFICIENTS

5.50215537E-02 -6.85059827E-02 -2.37738854E-01 -1.03186312E-01 -2.85056732E-01
-2.96380730E-01 -5.64080483E-01 -1.65139050E-01 4.22433162E-02 6.52872583E-02
1.13235555E-01 6.79437730E-02 2.32860157E-01 1.05605125E-01 3.18446447E-01
4.15954735E-01 -1.50909267E-02

THRESHOLDS

3.12405213E 00

PAIR 3 + NODE BAC B - NODE VEH V FISHER

COEFFICIENTS

-2.43349131E-02 2.17919791E-01 -3.62876007E-01 -2.74757127E-01 -4.80951073E-01
-2.85352412E-01 -8.36837909E-02 1.57472225E-01 -2.44472884E-03 -3.31949520E-03
2.57242412E-04 -1.74044409E-01 -1.87032597E-01 -4.68773417E-01 2.17216350E-02
-3.29597054E-01 -7.60738957E-02

THRESHOLDS

-2.43735551E 00

APPENDIX A (cont.)

```

*
*
*      PAIR 4      + NODE AER A      - NODE MAN M      FISHER
*
*.....*
*
*      COEFFICIENTS
*
*  -9.45035535E-02  -9.1455611AE-02  -3.24890064E-01  -3.34547005E-01  -3.47148104E-01
*  -4.14902347E-01  -5.14655415E-01  -2.66455295E-01  1.01819326E-02  7.19800948E-03
*  2.44770127E-02  2.3165115AE-02  4.24226176E-02  4.84183427E-02  6.91466619E-02
*  1.14901794E-01  -2.01041695E-02
*
*      THRESHOLDS
*
*  2.58700672E-01
*
*.....*
*
*      PAIR 5      + NODE AER A      - NODE VEH V      FISHER
*
*.....*
*
*      COEFFICIENTS
*
*  -1.92953674E-01  -5.07769891E-01  -3.55320920E-01  -4.19701312E-01  4.31834130E-02
*  -2.34944603E-01  -2.95311403E-01  9.42678319E-02  -1.33619983E-02  -2.55995505E-02
*  -3.46227533E-02  -7.71235606E-02  -2.06717148E-01  -3.78554143E-01  -4.67088893E-02
*  -2.12154316E-01  -8.56710370E-02
*
*      THRESHOLDS
*
*  -3.19489552E 00
*
*.....*
*
*      PAIR 6      + NODE AER A      - NODE HAC H      FISHER
*
*.....*
*
*      COEFFICIENTS
*
*  2.25317552E-01  -1.28312501E-01  -2.21627820E-01  -1.20584165E-01  -5.64296972E-02
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*  -3.48783544E-02  -6.81271860E-02  -2.78323909E-02  -1.15603563E-01  -1.91193383E-01
*  -1.49417957E-01  -2.96081842E-02
*
*      THRESHOLDS
*
*  -2.45968066E 00
*
*  END OF THIS LOGIC SET

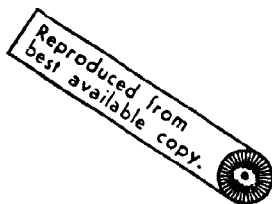
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APPENDIX B

PROBABILITY OF CONFUSION MEASURES

PAIR B/A RANKINGS

RANKING	MEASUREMENT	CONFUSION
1	17	.1421819474
2	12	.2652807392
3	5	.3072692964
4	6	.3165245203
5	16	.3249111585
6	11	.3730277186
7	13	.3859630420
8	8	.4012793177
9	7	.4149253732
10	14	.4182302772
11	10	.4370646766
12	9	.4761549394
13	4	.4780383794
14	1	.6012082445
15	3	.6181947406



PAIR V/H RANKINGS

RANKING	MEASUREMENT	CONFUSION
1	1	.1664475550
2	10	.1908978424
3	14	.2383677468
4	15	.2827314206
5	2	.2846003145
6	6	.3888717037
7	11	.3934066047
8	13	.4044028562
9	9	.4230531262
10	16	.4300904802
11	3	.4603665610
12	5	.4792488336
13	7	.5970020365
14	4	.6096074034
15	8	.6315959065

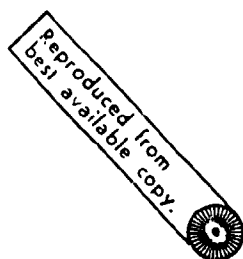
PAIR A/V RANKINGS

RANKING	MEASUREMENT	CONFUSION
1	17	.2833151837
2	6	.2847778276
3	5	.3128349668
4	8	.3428245041
5	1	.3664616830
6	7	.4208464117
7	4	.4939353999
8	14	.5092349412
9	16	.5092669699
10	9	.5102064783
11	11	.5250571178
12	12	.5904917473
13	13	.6157303611
14	3	.6421326843
15	2	.7200798583

PAIR B/V RANKINGS

RANKING	MEASUREMENT	CONFUSION
1	17	.0575622995
2	10	.0929928446
3	13	.1453737972
4	15	.1876634592
5	9	.1897606711
6	14	.1907475944
7	1	.2341598816
8	12	.2375277572
9	2	.2714162349
10	4	.2908709598
11	3	.2969035263
12	5	.3909943252
13	8	.4229336294
14	16	.4342709105
15	7	.5745743894

PAIR A/V RANKINGS



RANKING	MEASUREMENT	CONFUSION
1	17	.1485912517
2	14	.2684960750
3	10	.2892214637
4	13	.2965389935
5	9	.3099839148
6	3	.3141200975
7	4	.3321028560
8	2	.3362761013
9	15	.3607522219
10	5	.4015506979
11	8	.4069988955
12	1	.4649944035
13	16	.5499492243
14	6	.5644555139
15	12	.5790581661

PAIR A/B RANKINGS

RANKING	MEASUREMENT	CONFUSION
1	10	.3554874310
2	12	.5176272226
3	1	.5319538116
4	11	.6781218057
5	9	.6833537708
6	13	.6877375844
7	16	.6964030248
8	8	.7203964849
9	15	.7547721235
10	14	.7570713265
11	2	.7822194974
12	17	.7976190477
13	4	.8806560393
14	3	.8991518497
15	6	.9086557218

REFERENCES

- [1] Foley, D.H., "The Probability of Error on the Design Set as a Function of the Sample Size and Feature Size," Ph.D Dissertation, Syracuse University, June 1971, RADC-TR-71-171, AD738 648.
- [2] Sammon, J.W., "Interactive Pattern Analysis and Recognition," IEEE Transactions on Computers, July 1970.
- [3] Sammon, J.W., "An Optimal Discriminant Plane," IEEE Transactions on Computers, Sep 1970
- [4] Connell, D.B., et al., "Programs for On-Line Pattern Analysis," RADC-TR-71-177, Sep 1971, AD732 235-6.